Production Scheduling using Production Feedback Data; an Illustrative Case Study

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Abstract. Industry 4.0 is providing unprecedented opportunities for the capture and use of data into production planning and control (PPC). The accuracy of such data for PPC has been found to have a direct positive effect on operational performance. This study builds on a dynamic approach where production feedback data is used to improve the accuracy of master data used in tactical planning. The study applies a model-based approach using data from a real case. Two illustrative sensitivity analyses indicate that even small deviations in the accuracy of master data have an impact on the production schedule in terms of job sequence and makespan. The paper's main theoretical contribution is the development of six propositions on this relationship, where in short, the sequence appears to be sensitive to the accuracy of both changeover time and processing time. The paper illustrates how sensitivity analysis can be used in investment decisions about which production feedback data to capture and use for PPC purposes. Further research should test the propositions in more real cases and other production environments and carry out sensitivity analyses with more types of master data, variables, and combinations.

Keywords: Smart Production Planning and Control, Flexible Job Shop Scheduling, Case.

1 Introduction

The emergence of Industry 4.0 and increasing digitalization of operations provide new opportunities for production planning and control (PPC). The application of data from a more diverse range of sources has made way for more integrated, dynamic and real-time PPC, aptly labelled smart PPC [1-3]. A consequence of the growing application of digital technologies in production is a large increase in both the quantity and quality of data captured on the shopfloor [4]. Examples include data about the current statuses of active production jobs, utilized resources, and set-up and processing durations for process steps [5]. This operational data is typically used for control and monitoring of production in order to update short-term production plans, handle unexpected events, and monitor resource efficiency and production job statuses [6]. Further, the accuracy of such data for PPC has been found to have a direct positive effect on operational performance [7].

There is now a growing body of research on the use of this type of production feedback data for PPC, see for instance Oluyisola [8] , Schuh, Thomas [5], Schuh, Reuter [9], Reuter and Brambring [6], and Schäfers, Mütze [4]. These studies have mainly investigated the use of production feedback data on a conceptual level or for control purposes, while literature on its usefulness for tactical planning and scheduling is still scarce. A recent contribution on the topic is the conceptual model for application of production feedback data into tactical planning to improve planning quality [10]. The concept proposes the use of production feedback data to verify or dynamically determine master data used in tactical planning, such as processing times, changeover times and scrap rates. The next step is to test the concept in a real-life case.

The **purpose** of this paper is therefore to use data from a real case to *investigate the impacts of accuracy of master data for planning on a production schedule.* In particular, the study addresses the following **research question**: *how can the accuracy of production feedback data affect the sequencing of jobs in a flexible job shop production environment?*

To answer the research question, the study applies a model-based approach and sensitivity analysis using data from a medium-sized Norwegian food producer. In order to reduce the complexity of the scheduling problem, two types of master data were included in the optimization model: changeover time and processing time. Two sensitivity analyses investigate the impact of the accuracy of these two types of master data on the production schedule with regards to job sequence and makespan.

The paper's main theoretical contribution is the development of a set of propositions on the effects of the accuracy of changeover time and processing time on a production schedule. Additionally, some insights are provided for practitioners that can assist them in identifying the most beneficial production feedback data to capture and use for PPC purposes. The paper does not aim to develop new algorithms for scheduling but rather applies an existing mixed-integer linear programming (MILP) model and uses this as a tool for sensitivity analyses.

The study's scope is limited to the context of the case study. The production is make-to-stock (MTS) mainly based on forecasts, where production of standard products is organized in batches in a four-stage, flexible job shop environment with fixed routings.

In the next section, the theoretical background of the study is outlined. Section 3 describes the study's methodology and section 4 introduces the case. The model and results of the sensitivity analyses are presented in sections 5 and 6, before the conclusions and directions for further research are outlined in section 7.

2 Theoretical Background

2.1 Production Planning and Control (PPC)

PPC can be understood as the activities of loading, scheduling, sequencing, monitoring, and controlling the use of resources and materials during production [11]. Loading involves determining the amount of work to be done, while scheduling deals with determining the appropriate timing of tasks [11]. Sequencing is concerned with establishing the order in which tasks are to be performed. Monitoring and control focus on ensuring that tasks proceed as planned and taking corrective actions when necessary to maintain adherence to the plan [11]. Thus, PPC makes decisions about which products to produce in which quantities at which times to meet customers' demands [1].

The strategic planning level provides a broad and aggregated view of production operations in the long term, formulated in a master production schedule (MPS) [2]. This is then analyzed through rough-cut capacity planning to discover potential capacity problems and critical resources [12]. In the tactical level, the materials requirement planning (MRP) process combines the MPS with bill of materials (BOM) and inventory data to determine what to order, in which quantities, and at what time [2]. Based on the calculation of net requirements, production and purchase orders are generated. In addition, before the MRP is executed, capacity requirements planning (CRP) is performed to check that the required capacity is available. The operational level deals with the short-term planning, where the plan from the tactical level is scheduled and executed. This level is also concerned with monitoring of operations, dispatching, expediting, inspecting, evaluating, and taking corrective actions [11].

Most organizations worldwide have adopted enterprise resource planning (ERP) systems to integrate their processes and functions [13-15]. An ERP system supports a range of business functions such as production, procurement, material management, sales, and logistics [13, 15] and provides companies with an integrated database of transactions, business records and master data [16]. The quality of the planning processes, particularly on the tactical level, is highly dependent on the accuracy of the master data used in planning [17]. Master data identify and describe all the important business objects, e.g., business partners, employees, articles, BOM, lead-times, resources, and accounts. Typically, master data are created once, used many times and not frequently updated [17, 18], such that the master data used for e.g. MRP or scheduling might not accurately reflect the current state of the shopfloor [19]. This lack of accuracy in planning data can lead to discrepancies between a plan and its execution on the shopfloor.

Today, practically every production system is to a certain extent planned and controlled by ERP. However, many of the PPC decisions still rely on experts' experience [20], and they are often performed with the support of spreadsheet solutions [21].

2.2 Scheduling

Scheduling is the process that links the tactical and operational levels of PPC by allocating resources to perform a group of jobs over a period of time [22]. A schedule can therefore be considered as a list of starting times and machine assignments for each operation of each planned job [23]. Determining the best schedule might be simple or very complicated depending on the production environment, the process limitations, and the performance indicators [24].

Since the 1950s, the job shop scheduling problem (JSP) has been recognized as a challenging combinatorial optimization problem [25]. The JSP aims to generate a schedule of jobs in a multi-machine setting with predetermined operation sequences [26]. The extensive use of multi-purpose machines in real-world manufacturing systems has made it increasingly common for an operation to be controlled by multiple machines – a problem known as the flexible job shop scheduling problem (FJSP) [27]. FJSP, as an extension of JSP, was introduced by Brucker and Schlie [28] and is categorized into sequencing and routing subproblems [25].

The FJSP problem has received a lot of attention and has been well-studied in the last three decades (see e.g., [25, 29] for an overview). For instance, Framinan, Fernandez-Viagas [30] showed that rescheduling improves the performance of the shopfloor with low to medium variability in processing times, and that investments in capturing real-time data at the scheduling level could be worthwhile. Further, Fernandez-Viagas and Framinan [31] demonstrated that the advantages of using real-time, integrated data rely extensively on the appropriate selection of both the scheduling approach and the solution approach.

2.3 Smart PPC

Industry 4.0 technologies have led to the creation of enormous amounts of data and have the potential to revolutionize production operations [32]. Smart PPC is an emerging topic within PPC that incorporates such technologies and their capabilities into PPC by enabling real-time, data-driven decision-making and continuous learning with inputs from a more diverse range of data sources [2]. Smart PPC can enable flexible and responsive planning, scheduling, and control by tracking, gathering, evaluating, and managing data from internal and external sources [20].

A promising avenue for smart PPC is the exploitation of the access to data from the shopfloor into planning processes. In addition to increasing the accuracy, timeliness, and completeness of data used in planning, the access to such production feedback data can help to overcome some of the limitations of the hierarchical approach to PPC by providing feedback loops from lower planning levels into higher planning levels [2].

Due to the static nature of master data, the current state of the shopfloor is often not reflected in tactical planning [19], leading to potentially large deviations between the production plan and the actual execution on the shopfloor. In an attempt to overcome such weaknesses, Rahmani, Syversen [10] proposed a concept for the application of production feedback data in tactical planning to improve planning quality (see **Fig. 1**). This more dynamic approach to master data can both increase planning data accuracy and help to overcome some of the limitations of the hierarchical approach to PPC by feeding data about the situation on the shopfloor into higher planning levels. The concept further outlines how production feedback data can be used for two purposes in MRP: 1) to verify static master data, and 2) to determine dynamic master data. The concept remains to be applied in real-life cases.

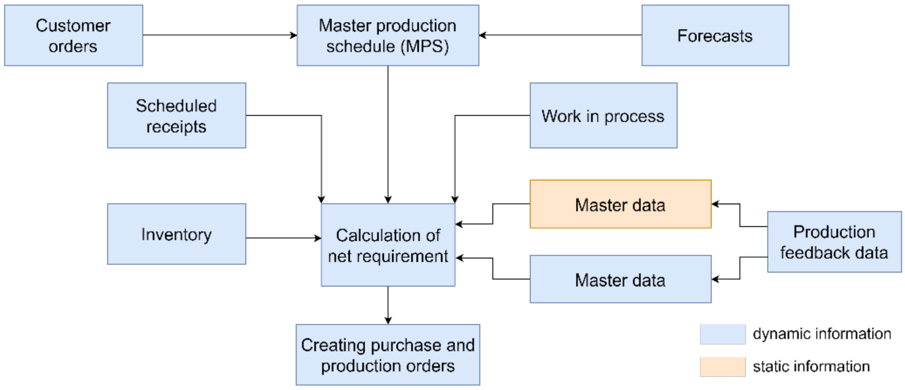

Fig. 1. Conceptual model for application of production feedback data into MRP [10].

2.4 Research Opportunities

The overview of the theoretical background for this study highlights some key challenges and interesting opportunities for research on production scheduling using production feedback data. Firstly, Industry 4.0 is providing unprecedented opportunities for the capture and use of data into PPC. Much of the literature has focused on the use of this for the operational planning level and less has been done on how production feedback data can be applied in scheduling as a link between tactical and operational PPC. Secondly, literature shows that tactical planning should not be based solely on static master data but also use production feedback data to dynamically determine master data that is variable. Thirdly, studies indicate that scheduling can be improved with the application of model-based approaches and use of more accurate and real-time data from the shopfloor. However, there is a need for more research to better understand the effects of the accuracy of master data for planning on the production schedule.

3 Methodology

In order to address the research opportunities identified in section 2.4, this study uses an illustrative case study of a Norwegian food producer. The company was selected because of their interest in the potential of using production feedback data for PPC purposes and the researchers' in-depth knowledge of the company's processes and PPC. The company’s nuts production was selected as the main focus for the study because of the data capture infrastructure already established on the nuts processing and packing machines. The main data collection for the study took place between August 2022 and April 2023. Qualitative data on products, production processes, material flows, and PPC processes was collected through observations and two site visits, several physical and online meetings, and formal interviews with two production planners, the supply chain manager, and the project manager. The case descriptions were validated by the nuts production planner. The qualitative data was jointly analyzed by the involved researchers to identify challenges and opportunities for PPC in the case. Quantitative data such as production plans, sales, forecast accuracy, and overall equipment efficiency (OEE) was extracted from the company's ERP and business intelligence systems and analyzed by the researchers. For the study, the company's current Excel-based scheduling procedure was implemented into a mathematical scheduling model. The model was validated manually using a simple example before it was used in the sensitivity analyses. Scenarios for the sensitivity analyses were run using realistic parameters for the nuts production. The results from the analysis were jointly analyzed by the researchers to develop a set of propositions.

4 Case Description

4.1 Introduction to the Company and its Production

Brynild AS is a medium-sized, family-owned producer of snacks, sugar confectionery, and chocolate products. The company has approx. 230 employees and an annual revenue of EUR 90 mill. The company's main customers are the three Norwegian grocery wholesaler–retailer dyads that control 100 % of the retail market, with wholesalers typically requiring a 98 % service level and two to three days delivery lead time. Consumer demand for the company’s products is highly seasonal and affected by a high frequency of promotional activities and new product launches. The company's factory in Norway produces approx. 80 variants of nuts, 40 variants of sugar confectionery products, and 50 chocolate variants. The products have a shelf-life of 5-24 months.

For nuts, there are 200 different inputs (raw materials and packaging materials), which are processed and packed into 80 variants of finished goods. The nut production is organized into four main integrated process stages: separating, cooking, mixing, and packing (see **Fig. 2**). Processing starts with separating, before cooking using either a dry roasting or frying machine. The cooking machines can be run in parallel, and based on the type of job, one of them is selected. After cooking, intermediates are either sent to mixing (where they are mixed with other intermediates) or directly to packing. After processing is complete, the finished intermediates are packed. There are five unrelated parallel machines in the packing stage, where each machine has specific capabilities regarding capacities and packaging types. There are no buffer inventory points between the processes, and all processed intermediates should be packed in the same day, although an intermediate can be stored for up to four days before packing.

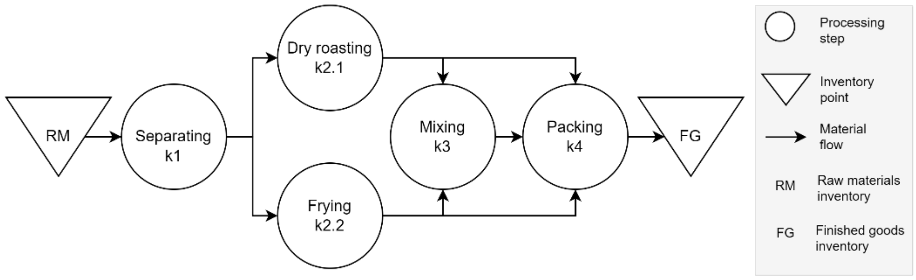

Fig. 2. Nuts production processes, stock points and material flow.

Brynild has a sensory system that captures real-time data from the nuts packing machines. Several types of data are captured in real-time, such as the start and finish time of batches, batch size in kilograms, amount of waste, stop times, and break times. The data is stored in the manufacturing execution system (MES). Parts of this data is currently used for calculation of OEE and as a basis for improvement efforts to identify breakdowns and other issues that reduce the capacity of the packing machines.

4.2 Production Planning and Control (PPC) in Brynild

PPC of nuts in Brynild. Brynild's production is primarily MTS for standard products, with some elements of make-to-order (MTO) for promotional campaigns. A production planner generates a weekly production plan for nuts based on a 26-week demand forecast extracted from the ERP system. The planner then calculates net requirements in Excel spreadsheets. Here, the weekly forecast is manually adjusted with finished goods inventory levels, required safety stocks, scheduled receipts, new product launches, planned campaigns, and seasonal demand.

After a rough-cut capacity check, the planner finalizes the weekly production plan for each product for the coming 10 weeks. Next, the planner manually determines the production schedule for the coming week, specifying sequences and volumes per product per shift per day. The planner starts by scheduling jobs on the packing machine because this has the lowest capacity. The resulting sequence is then applied in all the preceding stages. The schedule for the week is then printed and distributed manually to the shopfloor. Daily shift reports are sent back to the factory systems digitally.

In the scheduling, the processing time per intermediate is based on the planner's experience of the capacity of each machine per intermediate per shift. The planner uses rules of thumb for the sequencing of jobs based on the type of intermediates to be produced. The objective is to minimize changeover time, so for instance non-salted intermediates are produced before salted intermediates because this requires less changeover time. The most time-consuming changeover activity is cleaning (washing and drying) of machines, and the duration varies with the type of intermediate. Generally, only one type of intermediate is produced in each shift and cleaning takes place between shifts. When the same intermediate is produced in consecutive shifts, the machines do not need to be cleaned for three to four days. Before another intermediate is produced, four hours of cleaning time is typically required.

Challenges and Opportunities for PPC. Brynild's current PPC process is experience-based, with several manual tasks and application of informal rules of thumb. The master data currently used for planning is not systematically updated or verified, thus there is uncertainty about the accuracy of some of the input data used for planning and potential discrepancies between the issued production schedules and the execution of these on the shopfloor. Further, given that the planner is responsible for planning approx. 80 variants of finished goods in a flexible job shop environment, the scheduling problem is fairly complex. Thus, a model-based approach could be useful to generate higher performing schedules. The company already has an IT infrastructure for capturing real-time data on machines and has found useful ways to use this to improve OEE. However, the captured data could potentially also be used for PPC purposes. Thus, the company is a suitable case for investigating how production feedback data can be used to improve data accuracy and planning quality through model-based scheduling.

5 Scheduling Model

In order to investigate how the accuracy of production feedback data affect the sequencing of jobs in a flexible job shop production environment, a model-based approach was used. The main assumptions from the company's current scheduling procedure were implemented into a mathematical scheduling model. The model by Shen, Dauzère-Pérès [33] was used because it considers the assumption of sequence-dependent changeover times. Since all machines in the case are not capable of processing all operations for each job, a binary parameter was added to the model to guarantee that each operation of a job is assigned to an eligible machine. The objective of the applied model is to schedule a number of jobs on a set of machines to minimize the maximum completion time, i.e., the makespan (C_{max}). The model generates the initial sequence of jobs or schedules for the case.

The parameters, assumptions and decision variables of the scheduling model are formulated as follows. A set J of $\underline{n}$ jobs, where each has its own processing order, shall be processed on a set M of $\underline{m}$ machines. There are a number of n_i consecutive operations that have to be performed to complete the job i on any machine among a subset $M_{ij} \subseteq M$ of eligible machines. Let denote O_{ij} as the *j*-th operation of job *i,* and p_{ijk} be the processing time of operation O_{ij} on machine *k*. Changeover time is not negligible and depends on the sequences of the jobs. Changeover $s_{ii'k}$ occurs when operations of jobs *i* and i' are processed successively on machine *k*. All jobs and machines are available at time zero, and each machine can only execute one operation at a given time. Unlimited buffer capacity is considered between the machines. Preemption is not allowed, and transportation times are not considered in the model. Since each operation can be processed on one eligible machine, u_{ijk} and α_{ijk} are defined as a binary parameter and a binary variable, respectively. u_{ijk} is equal to 1 if machine *k* is capable to process operation O_{ij} and α_{ijk} is equal to 1 if operation O_{ij} is assigned to machine *k*. To model the problem, the following decision variables are required; t_{ij} as the starting time of operation O_{ij}, C_{max} as the makespan, and $\beta_{iji'j'}$ as a binary variable. It gets value 1 if operation O_{ij} is scheduled before operation $O_{i'j'}$.

According to the assumptions and notations mentioned above, the mathematical model is formulated as follows.

Minimization C_{max}

S.t.

$$\sum_{k \in M_{ij}} u_{ijk} * \alpha_{ijk} = 1 \qquad \forall i \in J, j \in 1, \dots, n_i \qquad (1)$$

$$t_{ij} = t_{i(j-1)} + \sum_{k\in M_{i(j-1)}} p_{i(j-1)k} * \alpha_{i(j-1)k} \qquad \forall i \in J, j \in 2,\dots,n_i \tag{2}$$

$$t_{ij} \geq t_{i'j'} + p_{i'j'k} + s_{i'ik} - \left(2 - \alpha_{ijk} - \alpha_{i'j'k} + \beta_{iji'j'}\right) * H \qquad \forall (i,i') \in J \times J, \forall\, j = 1,\dots,n_i, j' = 1,\dots,n_{i'}, \text{s.t. } O_{ij} \neq O_{i'j'}, k \in M_{ij} \cap M_{i'j'} \tag{3}$$

$$t_{i'j'} \geq t_{ij} + p_{ijk} + s_{ii'k} - \left(3 - \alpha_{ijk} - \alpha_{i'j'k} - \beta_{iji'j'}\right) * H \qquad \forall (i,i') \in J \times J, \forall\, j = 1,\dots,n_i, j' = 1,\dots,n_{i'}, \text{s.t. } O_{ij} \neq O_{i'j'}, k \in M_{ij} \cap M_{i'j'} \tag{4}$$

$$C_{max} \geq t_{in_i} + \sum_{k\in M_{in_i}} p_{in_ik} * \alpha_{in_ik} \qquad \forall i \in J \tag{5}$$

$$t_{ij} \geq 0 \qquad \forall i \in J, j \in 1,\dots,n_i \tag{6}$$

$$\alpha_{ijk} \in \{0,1\} \qquad \forall i \in J, j \in 1,\dots,n_i, k \in M_{ij} \tag{7}$$

$$\beta_{iji'j'} \in \{0,1\} \qquad \forall (i,i') \in J \times J, \forall\, j = 1,\dots,n_i, j' = 1,\dots,n_{i'} \tag{8}$$

The objective function minimizes the makespan. Constraint (1) ensures that each operation is assigned to one eligible machine. Constraint (2) presents the precedence relationships between the operations of a job. Constraints (3) and (4) state the requirement that two different operations cannot be done at the same time on machine *k*. Constraint (5) computes the makespan. Constraints (6), (7) and (8) determine the permitted domains of the decision variables.

6 Sensitivity Analyses

6.1 Introduction

Using the model described above, two illustrative sensitivity analyses were performed to investigate how changeover and processing time accuracy can affect the sequencing of jobs and, consequently, the makespan. To this end, an initial schedule with job sequence and makespan was determined by solving the model in section 5 with data and assumptions from the company. Then, a number of scenarios were generated and analyzed in the model, comparing the effects of different levels of data accuracy for changeover and processing time.

Scheduling is done weekly for the coming week. An analysis of historic production schedules in the case showed that the average number of jobs per week is five. Therefore, to generate the initial schedule, five jobs were selected to create a realistic set of jobs that can be produced in one week. Out of 76 potential jobs from the historic schedules, the jobs were selected using the following selection criteria: 1) select jobs packed on the same packaging machine (to reflect how scheduling is currently done in the company), 2) select jobs that are processed on four different machines, with a predefined operation (to include all stages in nuts processing and packing, see **Fig. 2**), 3) select jobs to include a mix of dry roasting and frying (to represent the variety in processing steps), 4) select jobs that can be completed in one day, where the overall processing time on all machines is less than two shifts (to ensure the schedule is feasible), and 5) all the jobs require a mixing process (to capture differences in changeover time between jobs on the mixing machine).

Next, data was collected for each of the five jobs with regards to changeover and processing times. The production planner's estimation of the processing time for a determined batch size for each job is used in the calculations. In the second processing stage, jobs 1 and 3 are assigned to machine $k_{2.1}$ and jobs 2, 4 and 5 to machine $k_{2.2}$. The required time to complete job 1 on the first, second, third, and fourth machine is 2, 4, 3 and 7 hours, respectively. In the same order, respectively 2, 3, 4, and 6 hours are required to complete job 2, whereas 1.5, 3.5, 3, and 5 hours respectively are needed to complete job 3. Finally, the required processing times to complete job 4 is 2, 3, 3, and 7 hours respectively, while job 5 needs 1.5, 4, 2.5, and 6.5 hours respectively to be completed.

Sequence-dependent changeover time is considered between jobs that are processed successively on each machine. The possible values for changeover time are 0.5, 1, 3.5, and 4 hours. No changeover time is needed on the first machine, and there is no changeover time between job 1 and job 3 on machine $k_{2.1}$. In addition, changeover is required only when jobs 4 and 5 are processed before job 2 on machine $k_{2.2}$

The proposed model is solved using GAMS 40.3.0 and run by CPLEX solver on a laptop computer with 2.30 GHz Intel Core i7 processor and 32 GB RAM in 0.09 seconds. The initial sequence is i5-i1-i4-i3-i2, resulting in a makespan of 41.5 hours.

Two sensitivity analyses are conducted to investigate the effects of accuracy of processing time and changeover time on the job sequence and consequently the makespan. Detailed explanation of the sensitivity analyses and definition of scenarios are presented in the following sub-sections.

6.2 Findings from the first sensitivity analysis

An initial sensitivity analysis was carried out to generate a general understanding of the relationship between the data accuracy and the schedule. The scenarios were generated with regards to the accuracy of both changeover time and processing time, expresses as the % deviation of these parameters from their initial values.

Two groups of scenarios were considered, where the values for changeover time and processing time were set to the same % accuracy for all the jobs on each machine and for all the jobs on all the machines simultaneously. The first group of scenarios investigated data values below those in the initial schedule, down to a 100 % accuracy as this is the lowest theoretical value of the parameter. The second group investigated data values higher than those in the initial schedule. Scenarios were generated until the makespan reached the maximum number of hours an intermediate can be kept in the production line, i.e., 64 hours (4 days x 8 hours per shift x 2 shifts per day). This resulted in a total of 433 scenarios.

The results of the sensitivity analysis on the effects of changeover time and processing time accuracy on job sequence and makespan are summarized in **Table 1** and **Table 2** respectively, while the effects on makespan are plotted in **Fig. 3**.

Table 1. Effects of changeover time accuracy of all machines on job sequence and makespan.

Accuracy	Sequence	Makespan (hrs)	Accuracy	Sequence	Makespan (hrs)
0	i5-i1-i4-i3-i2	41.5	0	i5-i1-i4-i3-i2	41.5
-20 %	i3-i1-i5-i4-i2	41.1	20 %	i5-i1-i3-i2-i4	42
-40 %	i5-i1-i3-i2-i4	40.7	40 %	i5-i1-i3-i2-i4	43
-60 %	i3-i1-i5-i4-i2	40.3	60 %	i5-i1-i3-i2-i4	44
-80 %	i3-i1-i5-i2-i4	39.9	80 %	i5-i1-i3-i2-i4	45
-100 %	i4-i2-i1-i5-i3	39.5	100 %	i5-i1-i3-i2-i4	46
			200 %	i5-i1-i3-i2-i4	51
			300 %	i5-i1-i3-i2-i4	58
			400 %	i1-i5-i4-i3-i2	64

Table 2. Effects of processing time accuracy of all machines on job sequence and makespan.

Accuracy	Sequence	Makespan (hrs)	Accuracy	Sequence	Makespan (hrs)
0	i5-i1-i4-i3-i2	41.5	0	i5-i1-i4-i3-i2	41.5
-20%	i5-i1-i3-i2-i4	33.8	10 %	i5-i1-i3-i2-i4	45.5
-40%	i5-i1-i3-i2-i4	26.6	20 %	i3-i1-i5-i4-i2	49.4
-60%	i5-i1-i3-i2-i4	19.4	30 %	i5-i1-i2-i4-i3	53.4
-80%	i1-i5-i4-i3-i2	12.8	40 %	i5-i4-i3-i1-i2	57.3
-100%	i1-i5- i3-i2-i4	5	50 %	i5-i1-i4-i3-i2	61.3
			55 %	i5-i1-i2-i4-i3	63.2

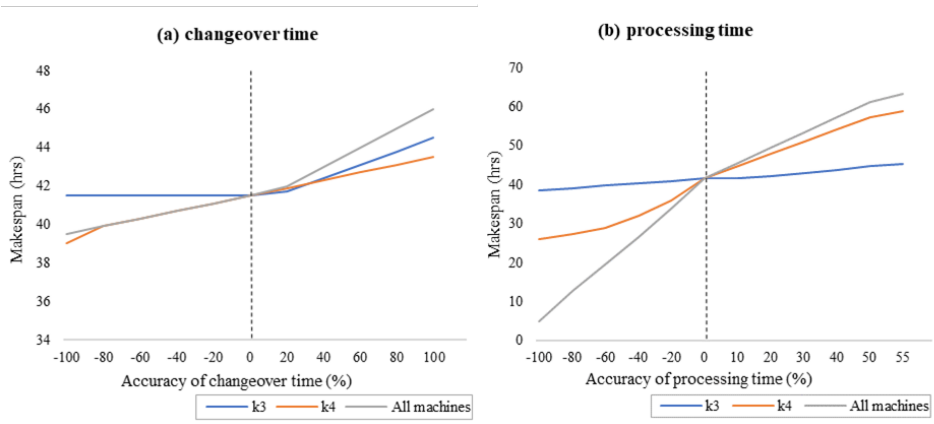

Fig. 3. Effects of accuracy of (a) changeover time and (b) processing time on makespan.

6.3 Findings from the second sensitivity analysis

The initial sensitivity analysis provided some general indications on the relationship between data accuracy and production schedules. To validate these findings, a second analysis was performed with more realistic and higher number of scenarios, particularly focusing on processing time as this is assumed to be more variable than changeover time in the case. Here, the scenarios investigated values of % accuracy for processing time individually for each job and on each machine. The accuracy of the values was investigated in both directions and for values up and down to 100 %, in increments of 5 %. This resulted in 800 scenarios and the results are summarized in **Fig. 4**.

The first column in **Fig. 4** shows the % accuracy of processing time in 20 % increments. As in the first analysis, the accuracy represents the % deviation of the parameter from its initial value. The initial sequence, i.e., i5-i1-i4-i3-i2, is shown in white. The other colors represent nine specific sequences that are different from the initial sequence, e.g., pink represents the sequence i5-i1-i3-i2-i4.

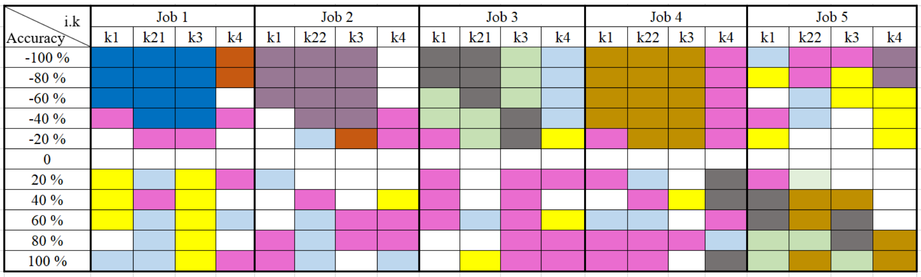

Fig. 4. Effects of processing time accuracy of each machine on job sequence

6.4 Propositions

The sensitivity analyses indicate that inaccuracy in processing time and changeover time can lead to changes in the optimal sequence. It was found that almost all changes in processing time for one job on a single machine has an impact on the sequence – which means that using a fixed sequence is less than optimal in a situation where processing times vary or are uncertain. Based on the analysis of the data, the following propositions are set forward regarding the relationship between the accuracy of changeover time and processing time on job sequence and makespan:

- P1: The <u>sequence</u> is very sensitive to the accuracy of **changeover** time for values lower than the initial schedule (0).
- P2: The <u>sequence</u> is not very sensitive to the accuracy of **changeover** time for values higher than the initial schedule (0).
- P3: The <u>makespan</u> is not very sensitive to the accuracy of **changeover** time, neither when the processing time is lower, nor higher, than the initial schedule (0).
- P4: The <u>sequence</u> is fairly sensitive to the accuracy of **processing** time for values lower than the initial schedule (0).
- P5: The <u>sequence</u> is very sensitive to the accuracy of **processing** time for values higher than the initial schedule (0).
- P6: The <u>makespan</u> is fairly sensitive to the accuracy of **processing** time both when the processing time is lower and higher than the initial schedule (0).

7 Conclusion and Directions for Further Research

This paper investigated the relationship between the accuracy of master data for planning and the performance of a production schedule. The findings indicate that even small deviations in data accuracy have an impact on a production schedule in terms of the jobs sequence and makespan. These initial analyses show that the sequence appears to be sensitive to the accuracy of both changeover time and processing time. Given that the determination of the sequence of jobs is the main decision made by production planners during scheduling, the study indicates that any improvements in the accuracy of master data used for planning should also be accompanied by a revision of the job sequence.

The study provides some useful insights and recommendations for the case company. Firstly, the company should start measuring and tracking the performance of their production schedules. There is also a potential to use production feedback data to validate or adjust the master data used in planning in general and in scheduling in particular. Further, the paper illustrates how sensitivity analysis can be used as a tool to create insights that can support strategic decision making, e.g., for investments in infrastructure for capturing data on the shopfloor. And finally, the company should consider replacing their current experience-based scheduling process with a model-based approach that can result in more optimal schedules.

The study has several limitations. Due to the NP-hard characteristic of the FJSP, mathematical modeling was found to be a useful initial step to understand the structure of the problem. However, it was not possible to reflect all assumptions from the case in the mathematical model, and the model was not tested with large amounts of real data from the company.

Further research should test the six propositions with real data from other cases and in other production environments. In addition, the sensitivity analyses had a limited scope and further research should investigate other parameters and different combinations of data accuracy on different machines, especially situations where the accuracy of different machines varies in magnitude and directions. To increase the generalizability of findings, the model should also be solved and run with a higher number of jobs – in more cases and other production environments. There is also a potential to extend the model with different objective functions (such as tardiness) and using heuristic algorithms to solve the model on a large scale. Further research should also address the integrated lot-sizing and scheduling problem to consider the effects of other types of master data for planning, such as scrap rate, capacity, and batch sizes.

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